Measuring Newspaper Readership: A Qualitative Variable Approach

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Audience measurement is critical for newspapers and other media. Newspaper readership is often measured by quantifying a particular indicator of the newspaper-reading activity. Example aspects include: whether the respondent *'read yesterday'* (Sharon 1973; Wang 1977; Straits 1991); *frequency*, 'number of times read newspaper _____ during the past [or typical] week?' (Burgoon, et al. 1980, 1981a, 198b; Schoenbach, et al. 1999); *time*, 'how much time would you say that you spend reading the newspaper?' (Loges 1993); completion, fraction of sections read (McCombs and Mauro 1977; Weaver and Mauro 1978); and *subscriptions* (Lain 1986).

The focus of these studies is either on causes or consequences of readership. An important, and neglected issue, however, is readership itself. Readership tends to be viewed far too simplistically. Usually a single question, such as frequency of use, is employed. Sometimes different questions are used but each one is analyzed separately. The use of single or separate questions, however, is problematic. At a minimum it should be obvious that multiple questions are ordinarily preferable to a single question measure. Beyond this, we have argued (Calder and Malthouse, 2002) that readership should be viewed as itself a construct that has many indicators.

Readership can be expressed in many ways. For instance, the frequency question above is certainly an indicator of readership. But is the usage behaviour of a person who read a newspaper twice halfway through different from that of a person who read the newspaper once all the way through? We contend that the behaviour may be the same. And ordinarily it is this behaviour that is of interest, not differences in how the behaviour is expressed. It is the construct of readership that is of real interest, not one or even multiple manifestations of it. Calder and Malthouse (2002) investigate this and show that a straightforward quantitative metrical scale approach can be developed to measure readership. We term these Reader Behaviour Scores (RBS).

The focus here is on a methodology we believe could be of wide applicability in audience measurement. We develop a qualitative variable approach to measuring readership. This has the benefit of not only providing a conceptually richer dependent variable as discussed above, but also one that reveals readership in a more descriptively interpret-

Abstract

Newspaper readership is usually measured by a single variable such as frequency of use, amount of use, etc. This article argues that readership cannot be fully described by a single measure and suggests treating it as a latent variable reflecting the time, frequency, and completeness of readership on both Sundays and weekdays. This study uses data from 101 newspaper markets in the US. The latent variable can be either quantitative or qualitative. Factor analysis is used to define the quantitative variable and latent class analysis, the qualitative variable. The relationship between the approaches is studied with principal components analysis, profiling, and hierarchical linear models. The two approaches are shown to produce complementary conclusions when relating readership to demographics and content interests. Media consumption studies can examine both qualitative and quantitative latent variables and thereby enhance the interpretability and the scope of the results.

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able way. The approach adds information to and complements the use of metrical approaches that yield a score on an abstract continuum.

The context of this study is newspaper readership. Although our focus here is methodological, we comment on the application of our results to increasing newspaper readership, which is in decline.

A qualitative variable approach to behaviour scores

We propose the following statistical methodology for identifying qualitative behaviour scores for, in our case, newspaper usage data.

Consider the behaviour of reading a newspaper. Assume a sample of n people and that manifestations of the behaviour have been measured on these people. In the newspaper data discussed in more detail in the next section, we measure six manifestations of newspaper readership: time, frequency, and level of completion for weekday editions and, separately, for Sunday editions. There are two approaches to developing behaviour scores for such data. One approach is to assume a quantitative latent variable and estimate a factor analysis model. The other approach is to assume a qualitative latent variable. The qualitative approach could be implemented with any discrete latent variable analysis such as k-means cluster analysis. A problem arises, however, in that in many cases one or more of the indicators of behaviour will be categorical. This implies the use of latent class analysis. Since this technique and programs for it are not widely available, we will present the model here for which we have developed a software implementation.

The details of this model are as follows. Denote the responses of some respondent to our six manifestations of readership by $\mathbf{x}=(x_1, ..., x_6)'$. Assume that every subject can be assigned to an unobserved type $k \in \{1, ..., k\}$ based on the observed manifestations $\mathbf{x}$. Since latent class analysis assumes that all manifest variables are discrete, we will form bins for metrical manifest variables. For example, the first question is the amount of time that someone spends reading weekday papers and we form three bins, 0 minutes, 1-30 minutes, and more than 30 minutes. Accordingly, if x_1 is weekday time then it takes values 0, 1, and 2. Let $\pi_{j|ik}$ be the conditional probability that an individual responds to question i in category j given membership in class k, i.e., $P(x_i=j\,|\,k)=\pi_{j|ik}$. Given class membership, the response to question i has a multinomial distribution with probabilities $\pi_{j|ik}$. Let η_k be the unconditional (prior) probability that an individual is in class k. Assume that given class membership, the responses to questions i and $i' \neq i$ are independent (axiom of conditional independence). Under these assumptions, the probability of $\mathbf{x}$ is

$$f(\mathbf{x}) = \Sigma_k \, \eta_k \prod_i \pi_{j|ik}.$$

Estimating latent class models is problematic because of local minima and a lack of good starting values. To our knowledge, no major statistical package offers latent class software. We have developed software to estimate the above model following Bartholomew (1987, pp. 28-30) (available from our web site). The software estimates parameters η_k and $\pi_{j|ik}$ under maximum likelihood. To address the problems of local minima and starting values the software estimates the model multiple times using different random starting values. In the analysis presented here, we estimated the solution using 50 sets of starting values.

Method

This study examines data on newspaper readership based on a representative sample of daily US newspapers and consumers.

Sampling

Details of the sampling methods are in Calder and Malthouse (2002) and will be briefly summarized here.[1] The first step of the sampling process was to select a representative sample of daily newspapers in the US. We compiled a sampling frame of 846 daily papers and stratified by circulation, competition, urbanicity, and extent of geographic distribution (number of zip codes). We drew a random sample of 101 newspapers with approximately the same number of large and small newspapers.

The second step of the sampling procedure was to draw a random sample of consumers from each of the 101 markets. We drew names from postal codes accounting for 80% of circulation within each newspaper's market. The sampling frame of consumers was a list compiled by a direct marketing list provider. We mailed 115,890 surveys. The individual in the household 18 years or older with the most recent birthday was asked to complete the survey. An incentive of $3 was attached to each survey, and responders were entered into drawings for 15 cash prizes. In total, 37,036 responded, giving a response rate of 37% after removing undeliverable surveys. The distribution of the number of responses in each market was normal shaped with a mean of 337, standard deviation of 46, minimum of 271, and maximum of 472.

The last step in the sampling procedure was a telephone survey of non-responders to the consumer mail survey. This was done to determine if non-responders were systematically different from responders. The phone survey was an abridged version of the mail survey to a random sample of 2000 non-responders, with approximately 20 from each market. We found that non-responders were more likely to be non-readers. The results of the phone survey along with age and sex information from the Census were used to compute sampling weights.

Readership data

The question wording and response coding is given below. Note that the latent class analysis described below required that the original response categories be collapsed.

1. *Weekday Time* (WD Time). How much time do you spend on an average weekday (Monday – Friday) reading or looking into the _____ newspaper? 'Do not read' and then 15-minute bins. (Recoded into response categories 0 = "Do not read," 1 = "1-30 minutes," and 2 = "31 minutes or more.")
2. *Sunday Time* (Sun Time). How much time, if any, do you spend reading or looking into any part of the _____ newspaper on an average weekend plus any time during the week? 'Do not read' and then 30-minute bins. (Recoded 0='Do not read,' 1='less than 1 hour,' and 2='1 hour or more.')
3. *Weekday Frequency* (WD Freq). Since the first of the year, which days do you read or look into the _____ newspaper in an average 7-day week? Check boxes for days of the week. (Recoded 0=none, 2='every weekday,' 1 otherwise.)
4. *Sunday Frequency* (Sun Freq). (Recoded 0=no, 1=yes.)
5. *Weekday Completion* (WD Comp). How much of the _____ newspaper do you read or look into on an average weekday? None, 1/4, 1/2, 3/4, All. (Recoded 0=none, 1='1/4 or 1/2,' 2='3/4 or All.')
6. *Sunday Completion* (Sun Comp). Same as weekday.

Results

We seek to show that qualitative and quantitative approaches to identifying behaviour scores complement each other. By this we mean that a qualitative latent variable can add information to and further explain a quantitative continuum of behaviour scores.

We applied latent class analysis as described to the six manifestations yielding nine distinct types of reader behaviour. To distinguish these reader behaviour scores from those obtained with a metrical approach (RBS), we refer to them as reader behaviour type scores or RBT. The decision to have nine types was made by comparing the log-likelihood values of the best k=3, ..., 12 class solutions and interpreting each. The results are described in Table 1, which gives the parameter estimates from the analysis. The first row in the table gives the percentage in each type (prior probabilities). For example, 21% of the population is in type 1. As shown in row two, 10,708 people in our sample were assigned to this type. Assignments were made to the type with the largest posterior probability.

Table 1: Reader Behaviour Types (RBT). Estimates of the percentage in each type (prior probabilities η_k), sample sizes (n_k), and probabilities of different responses to the six questionnaire items by RBT membership ($\pi_{j|ik}$)

		RBT Scores (Latent Class number k)								
Variable (*i*)	**j**	1	2	3	4	5	6	7	8	9
Percent (η_k)	**–**	0.21	0.28	0.08	0.06	0.06	0.11	0.1	0.03	0.07
n_k	**–**	10708	6370	2529	1675	1418	6630	3405	1420	1688
WD Time	**0**	0	0.95	0.03	0	0.89	0	0.01	0.04	0.66
	1	0	0.05	0.66	0.3	0.1	0.82	0.88	0.66	0.34
	2	1	0	0.31	0.7	0.02	0.18	0.11	0.3	0.01
Sun Time	**0**	0.01	0.98	0.03	0.01	0.02	0.01	0.06	0.6	0.16
	1	0.24	0.02	0.5	0.46	0.43	0.65	0.86	0.37	0.82
	2	0.75	0	0.48	0.52	0.55	0.34	0.09	0.03	0.02
WD Freq	**0**	0.01	1	0.18	0.02	0.83	0	0.08	0.01	0.76
	1	0.08	0	0.82	0.17	0.16	0.06	0.54	0.81	0.22
	2	0.92	0	0	0.81	0.01	0.94	0.38	0.18	0.01
Sun Freq	**0**	0.01	0.99	0.1	0	0.02	0.01	0.11	0.96	0.14
	1	0.99	0.01	0.9	1	0.98	0.99	0.89	0.04	0.86
WD Comp	**0**	0	1	0.04	0.01	0.98	0	0	0.18	0.86
	1	0.05	0	0.56	0.98	0.01	0.14	0.99	0.51	0.12
	2	0.95	0	0.4	0.01	0.01	0.86	0.01	0.31	0.02
Sun Comp	**0**	0	0.99	0	0.03	0	0	0.01	0.94	0.25
	1	0.11	0.01	0.26	0.97	0.38	0.13	0.99	0.06	0.75
	2	0.88	0	0.74	0	0.62	0.87	0	0	0

To interpret the nine types, we must examine the types in terms of the original six questionnaire items given above. The relevant results are shown in the bottom portion of Table 1. For example, the probably that someone in type 1 has a weekday time (the first questionnaire item) of '2' is 1.00. Likewise, the probability that someone in type 4 has a weekday frequency (questionnaire item 3) of '1' is .17.

1. *Heavy*. High on all aspects.
2. *Non-readers*. Low on all aspects.
3. *Sunday, Weekday Sometimes*. For Sunday, spends moderate to large amounts of time and reads completely. For weekday, reads only a few days a week and spends moderate to large amounts of time when they read.
4. *Selective Heavy*. Reads paper every day and spends a large amount of time, but only reads 1/4-1/2 of the paper.
5. *Sunday Heavy*. High or moderately high Sunday readership.
6. *Skimmer Heavy*. High frequency and completion, but moderate time.
7. *Light Selective*. Moderate on all aspect of readership.
8. *Weekday Sometimes*. Some are light and other heavy on time and completion variables.
9. *Sunday Only Light*. For Sunday, spends moderate amount of time and reads small fraction of paper. Rarely reads weekdays.

Calder and Malthouse (2002) developed a quantitative latent variable, reader behavior score (RBS), from the six manifestations of readership using factor analysis. The analysis found RBS to be unidimensional, highly reliable, and valid. RBS is on a 1-7 scale, where 1 indicates a non-reader of the newspaper and 7 the ultimate heavy reader.

We now show how the quantitative and qualitative analyses of the six manifestations of readership are related and how the RBT scores add to the interpretation of RBS. Figure 1 shows the distribution of RBS. The vertical lines show the average value of RBS for each RBT. For example, Non-readers have an average RBS of about 1.0, while Heavy readers have an average RBS of 5.9. The RBT scores fall along the RBS continuum but have different qualitative behaviour.

People with the highest RBS read more often, spend more time reading, and read more completely. Skimmer Heavy readers have somewhat lower RBS and spend less time with the paper, although they read frequently and completely. Selective Heavy readers have slightly lower RBS. Thus, there are differences in both the overall quantity of behaviour and the qualitative kind of behaviour. This qualitative information would not be apparent from the quantitative RBS alone.

It is also of interest to note that where the mean RBS for two RBT scores is similar, there are still revealing qualitative differences that are obscured by the RBS values. The RBS means for Sunday Only Light and Weekday Sometimes are approximately equal. But Table 1 shows there are differences between the two. There is an 86% chance that a Sunday Only Light reads on Sunday while there is a 4% chance that a Weekday Sometimes reads on Sunday. There is a 76% chance that a Sunday Only Light is a non-reader during the week, but only a 1% chance that a Weekday Sometimes is a non-reader during the week. Similar RBS values can reflect qualitatively different types of behaviour.

Figure 1: Distribution of RBS with average RBS value for each RBT

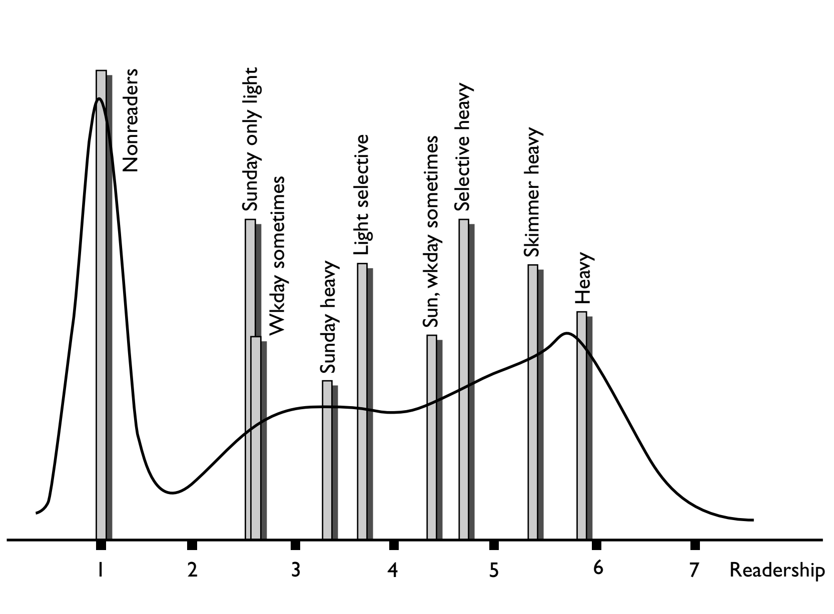


Figure 1 plotted the means of the conditional distributions of RBS given RBT. Figure 2 compares these conditional distributions in more detail with boxplots, sorted in ascending order of average RBS. There is substantial overlap in the distribution of RBS across the classes, suggesting that the measures are not equivalent. The RBT qualitative measure captures aspects of readership that are not captured by the RBS quantitative measure.

Everitt (1993, section 2.6.1) shows how principal components analysis (PCA) can be used to visualize a high-dimensional cluster analysis. We follow this PCA approach to visualize the latent class solution and to understand further the relationship between the quantitative RBS and qualitative RBT scores. As we shall see, some of the variation considered specific variance in the factor analysis model for RBS is important in defining RBT.

Table 2 gives the eigenvalues and eigenvectors (scaled to have unit length) of the correlation matrix.

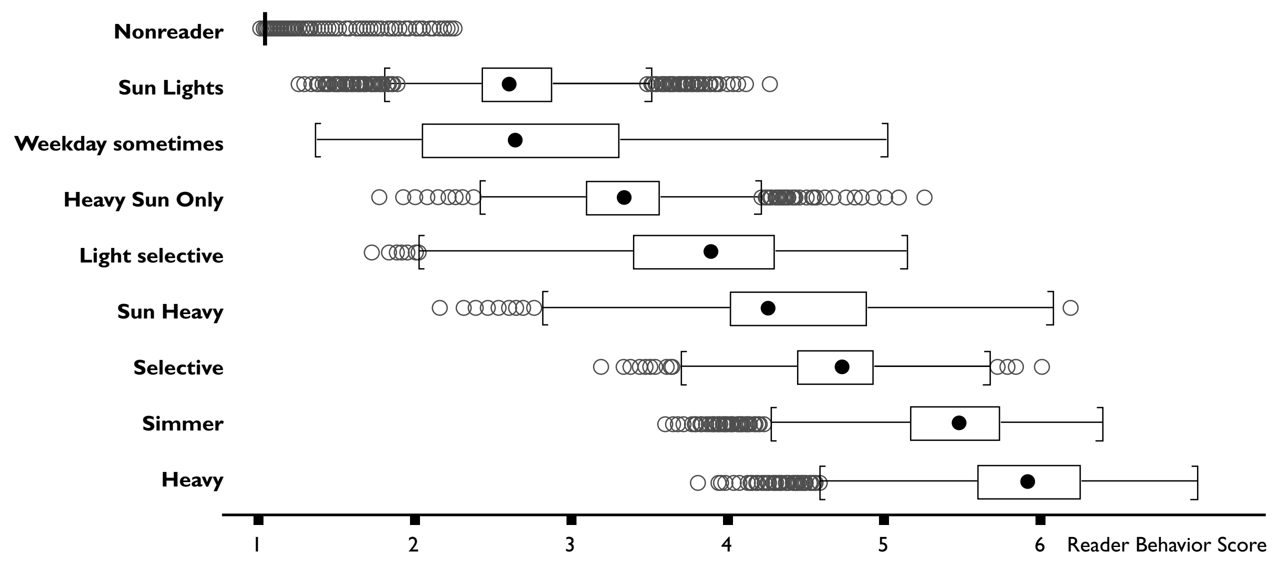
Table 2: Principal components analysis of correlation matrix between 6 readership questions

	Eigenvector		
Variable	1 RBS	2 Sunday vs Weekday	3 Skimmer vs Selective
Weekday time	0.41	-0.38	0.53
Sunday time	0.39	0.43	0.62
Weekday frequency	0.41	-0.45	-0.14
Sunday frequency	0.39	0.51	-0.24
Weekday completion	0.43	-0.35	-0.31
Sunday completion	0.42	0.28	-0.41
Eigenvalue	4.39	0.59	0.39

1. *RBS*. The elements of the first eigenvector are nearly equal, suggesting the first principal component is approximately proportional to a simple average of the standardized questions. RBS is the simple average of the six questions using a different method of standardization, so we expect the first principal component and RBS to be highly correlated. They are with $r > .998$. Therefore, the first principal component essentially is a linear transformation of RBS. This corroborates the factor analysis reported in Calder and Malthouse (2002). This component is the only one with an eigenvalue greater than 1, which further supports the unidimensionality claimed in Calder and Malthouse.
2. *Sunday vs. weekday*. The second eigenvector contrasts Sunday with weekday readership. Positive values of the second principal component indicate a Sunday-only reader, negative values indicate a weekday-only reader, and values near 0 indicate a balanced reader.
3. *Skimmer vs. selective*. The third eigenvector contrasts time with completion, and, to some extent, frequency. Positive values indicate selective reading: spending much time with a portion of the newspaper. Negative values indicate skimming: reading the entire newspaper in a short amount of time. Values around 0 indicate a balanced reader.

We can understand the relationships among RBTs better by computing the means of the six questions for each RBT and plotting these means in the three-dimensional subspace spanned by the first three eigenvectors.[2] Examination of Table 2 reveals the second two principal components account for far less, but some, variance. The variance in the second two components is not accounted for by RBS since the first component is essentially RBS. The interpretation is that the second two

Figure 2: Comparison of the distributions of RBS across RBTs



components reflect variance in the original six questions that is not captured by RBS. The type means are plotted in Figure 3. Although RBS captures 73% of the variation in the data, the figure shows that RBT reflects the second and third component as well as the RBS component. Weekday Sometimes and Sunday Lights have comparable RBS levels, but their readership is very different. In addition to reading different days of the week, the former appears to be a bit more selective than the latter. There is great overlap between the RBS values of Skimmers and Selectives, yet the two differ greatly on the third principal component.

Thus we see that the RBT qualitative measure does capture meaningful information considered noise in the RBS quantitative approach. Moreover, Figure 3 shows the RBT measure provides a more descriptive picture of behaviour. We further illustrate the usefulness of RBT in terms of its relationship with other variables in the sections below.

Demographics: RBT compared to RBS

We first examine demographic variables. Table 3 gives the averages of five demographic variables for different values of RBT. We computed the posterior distribution and assigned each person to the type with the largest posterior probability. The complete posterior distribution, class assignments, and question wording are available from our web site. For example, non-readers have an average of 14.6 years of education, an average household income of $55,700, and are 51.9% female. To quantify the strength of the relationship between RBT and each demographic variable, we report R^2 values from a one-way ANOVA models with RBT as the independent variable and the demographic as the dependent variable. The strength of the relationship between RBS and the demographics are quantified by the R^2 values from a regression of RBS on the demographic. Overall, there is a weak relationship between the demographics and readership (RBS or RBT).

Age varies the most across types for the five variables considered her. The oldest type is Heavy. The youngest types are Sunday Only Light, Light Selective, and Sunday, Weekday Sometimes. The relationship between age and RBS is much weaker (R^2=.0303) than its relationship with RBT (R^2=.0994). To understand these differences we computed the correlations[3] between age and the six manifestations of readership. The correlation of age with Sunday completion is .1874, weekday completion .2472, Sunday frequency .0786, weekday frequency .2427, Sunday time .1777, and weekday time .3123. Age is thus more highly correlated with weekday than Sunday readership. The correlation between Sunday frequency and age is particularly small. Studies that operationalize readership with frequency should find smaller correlations than those that operationalize readership with time.

The *sex* variable is also interesting. Previous demographic studies have found little difference between the readership of males and females and the R^2 value with RBS is .0001. But there are some differences across RBTs. In relative terms, the R^2 value with RBT (.0069) is many times greater, although it is still small in absolute terms. The Sunday Heavy, Sunday, Weekday Sometimes, and Sunday Only Light tend to be a bit more female; Weekday Sometimes tends to be more male. *Length of Residence* also varies considerably across types. Heavy readers have the largest average length of residence. The RBT with the highest income is Skimmer Heavy, followed by Selective Heavy and Light Selective. *Income* varies somewhat across the groups. Skimmers and Selectives tend to have higher income than the other groups. *Education* differences across groups are small.

Content interests by RBT

We now examine which content sections different RBTs read. The questionnaire included the following question: 'please indicate how important each section is to you personally by checking one box in the importance section for each type of content.' (1='Little/None,' 2='Some,' and 3='A lot') The survey included 30 content areas (question wording on the first author's web site).

Figures 4 and 5 show the average of importance for each content category by RBT. This information can be interpreted more easily with a linear model (Cleveland 1993, pp. 308-319). Let μ_{ij} be the average importance for content category i=1, ..., 30 and RBT j=1, ..., 9; note that μ_{ij} is plotted in Figures 4 and 5. We decompose μ_{ij} with a two-way ANOVA model without any interaction term:

$$\mu_{ij}=\mu+\alpha_i+\beta_j+e_{ij},$$

where μ is the grand mean, α_i is the effect of content category i, β_j is the effect of RBT j, and e_{ij} is the residual. The quantity $\mu+\alpha_i$ is approximately the simple average importance of content category i, ignoring RBT. The quantity $\mu+\beta_j$ is approximately the simple average importance assigned by RBT j across all content areas. Estimates of α_i and β_j are plotted in Figure 6, sorted in descending order of effect size.

The ordering of the content categories reflects the overall importance of each category across all RBTs or content categories. Weather is the most important content category across RBTs and Fashion/Beauty the least important. Across all content categories, non-readers gave by far the lowest importance ratings.

The residuals (e_{ij}) are plotted in Figures 7 and 8. Large deviations from 0 (solid line) are interesting. Positive residuals (dots to the right of the dashed line) indicate that a particular RBT is more likely to give a high importance rating to a particular content category. For

Figure 3: Scatterplot showing the class means in the subspace spanned by the first three eigenvectors

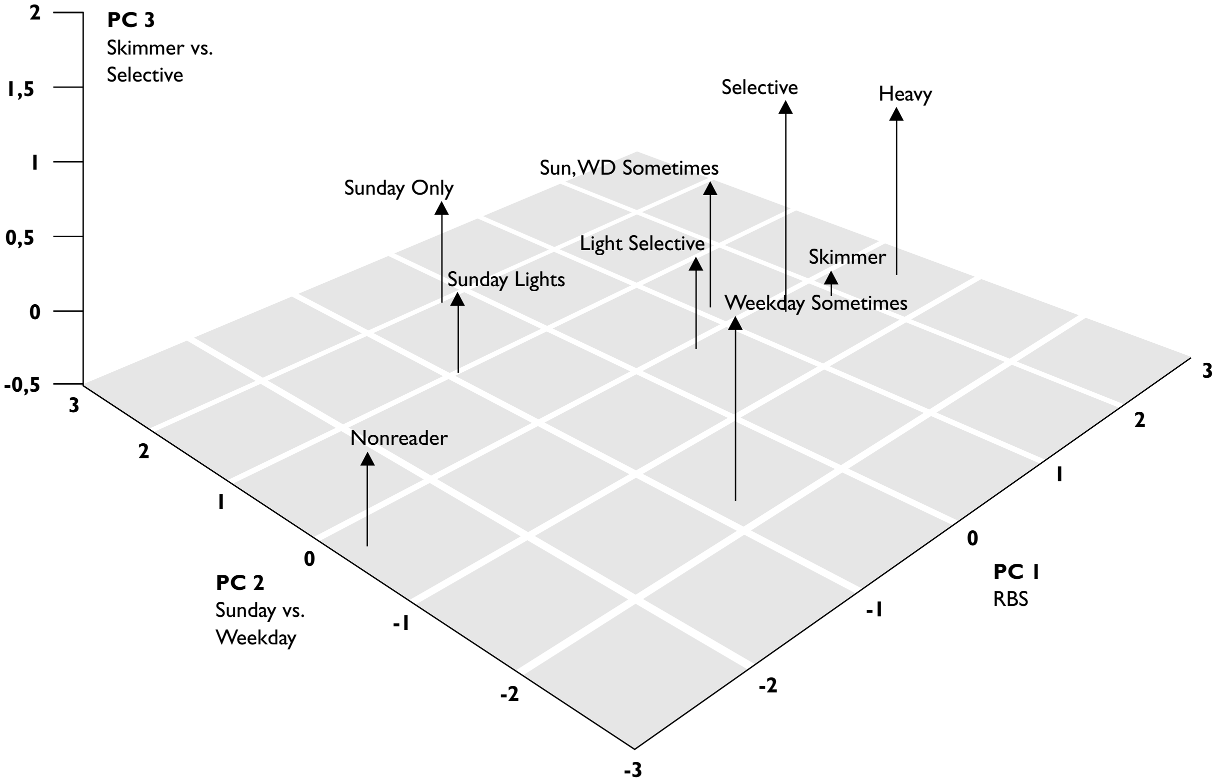


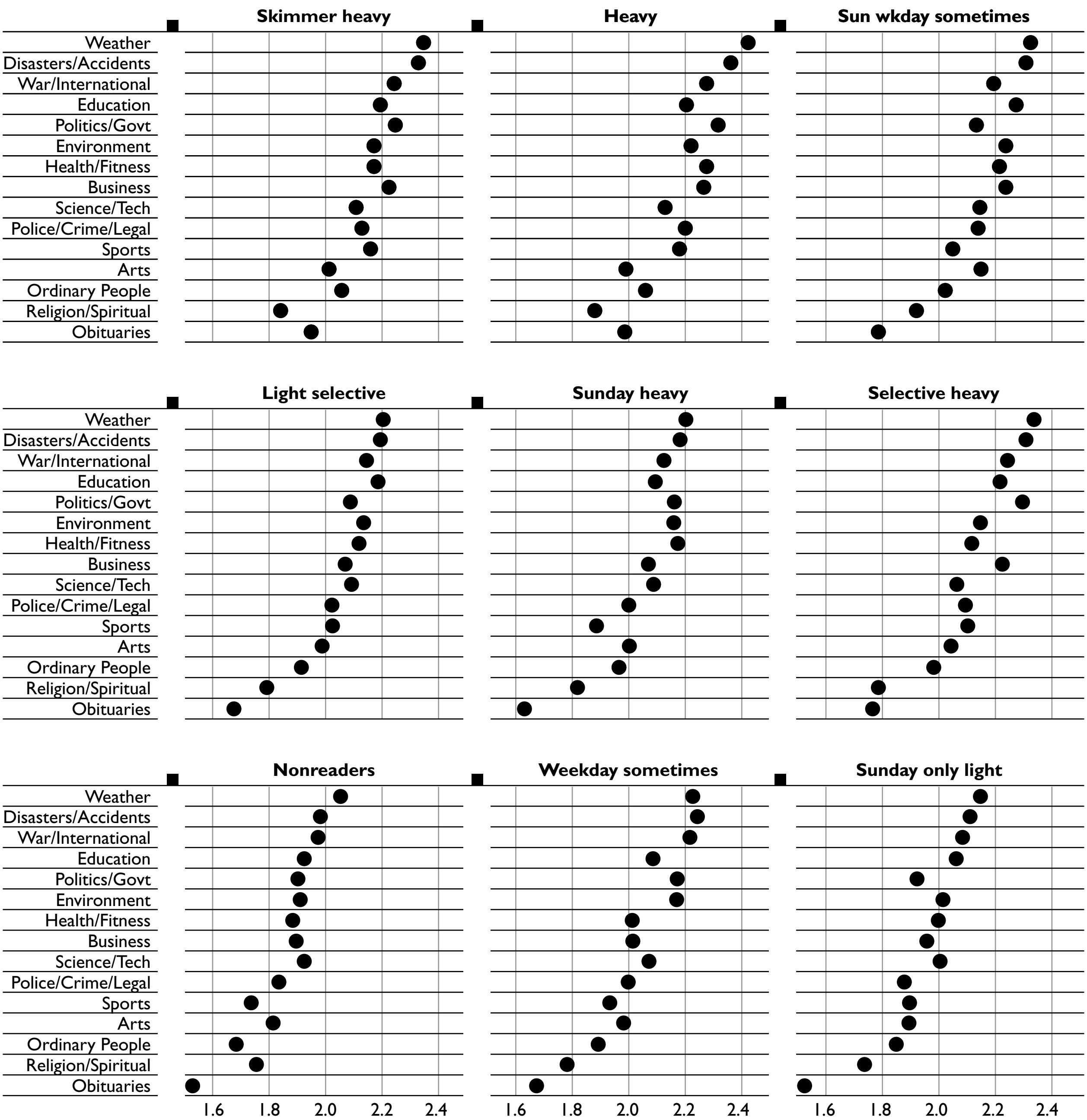
Table 3: Demographic relationship with RBT: years of education, annual household incomes (thousanda of dollars), percentage female, lenght of residence in community (years), and age in years

RBT	Age	Residence	Female	Income	Education
Non-reader	47.4	17.7	51.9	55.7	14.6
Sunday Only Light	40.9	14.9	56.7	61	14.8
Weekday Sometimes	47.2	18.3	43	54.1	14.8
Sunday Heavy	44.8	17.4	59.7	58.7	14.8
Light Selective	41.9	17.3	46.9	62.8	14.9
Sun, Weekday Sometimes	41.5	16.8	58.9	58.4	14.9
Selective Heavy	49.4	20.2	46.5	64	15.3
Skimmer Heavy	49.6	22.6	52	67.1	15
Heavy	57.4	27.4	49	59	14.7
Population Mean	48.3	20.2	51.5	59.4	14.8
ANOVA R^2 values	0.0994	0.0551	0.0069	0.0113	0.0051
RBS R^2 values	0.0303	0.0356	0.0001	0.0062	0.001

example, consider Sunday Only Light (lower right corner of Figure 7). This group has large residuals for Jobs/Career, Classifieds, Ads Stores, and Ads Food; this makes good sense because Sunday newspapers are usually good sources for these content areas. The Weekday Only group has negative residuals for Ads Food and Ads Stores, and weekday papers are often not so filled with this type of content.

Heavy readers are not so interested in Classified or Jobs/Career sections, but are a bit more interested in Food and TV sections. Sunday, Weekday Sometimes readers are particularly interested in advertisements for food, events, stores, and jobs, and classifieds, but not so interested in hard-news sections. Selective Heavy readers are interested in most kinds of hard news, especially on politics, government, business, and sports, and are not so interested in classifieds, advertisements for stores and jobs. Sunday Heavy readers are particularly interested in advertisements for food and stores, classifieds, and special sections of the newspaper, but not so interested in hard news. Skimmer Heavy readers are very interested in local news (community, obituaries, sports) but not so interested in jobs or classifieds. Light Selective readers are

Figure 4: Average importance of the first group of content categories by RBT



interested in jobs/career, Popular music, classifieds, and advertisements for events and movies. Weekday Sometimes readers are mostly interested in hard news sections and have little interest in most advertising or special sections. Sunday Only Light readers are mostly interested in advertisements, classifieds, and jobs/career.

We also computed correlations between the quantitative RBS variable and the importance ratings of the content areas. The correlations range from -.06 (classifieds) to .28 (obituaries) and are rather uninteresting compared with the analysis using RBT given in Figures 6-8.

Conclusion

Newspaper readership, as with other media consumption, is a construct that must be studied through its manifestations. We have employed six manifestations of reader behaviour: time, frequency, and completion for weekend and weekday editions. Restricting attention to a single manifestation gives an incomplete measurement of behaviour. Factor analysis or latent class analysis models can both be estimated on these manifestations, resulting in a quantitative latent variable or qualitative latent variable. This study demonstrates the value of doing both. The quantitative

Figure 5: Average importance of the second group of content categories by RBT

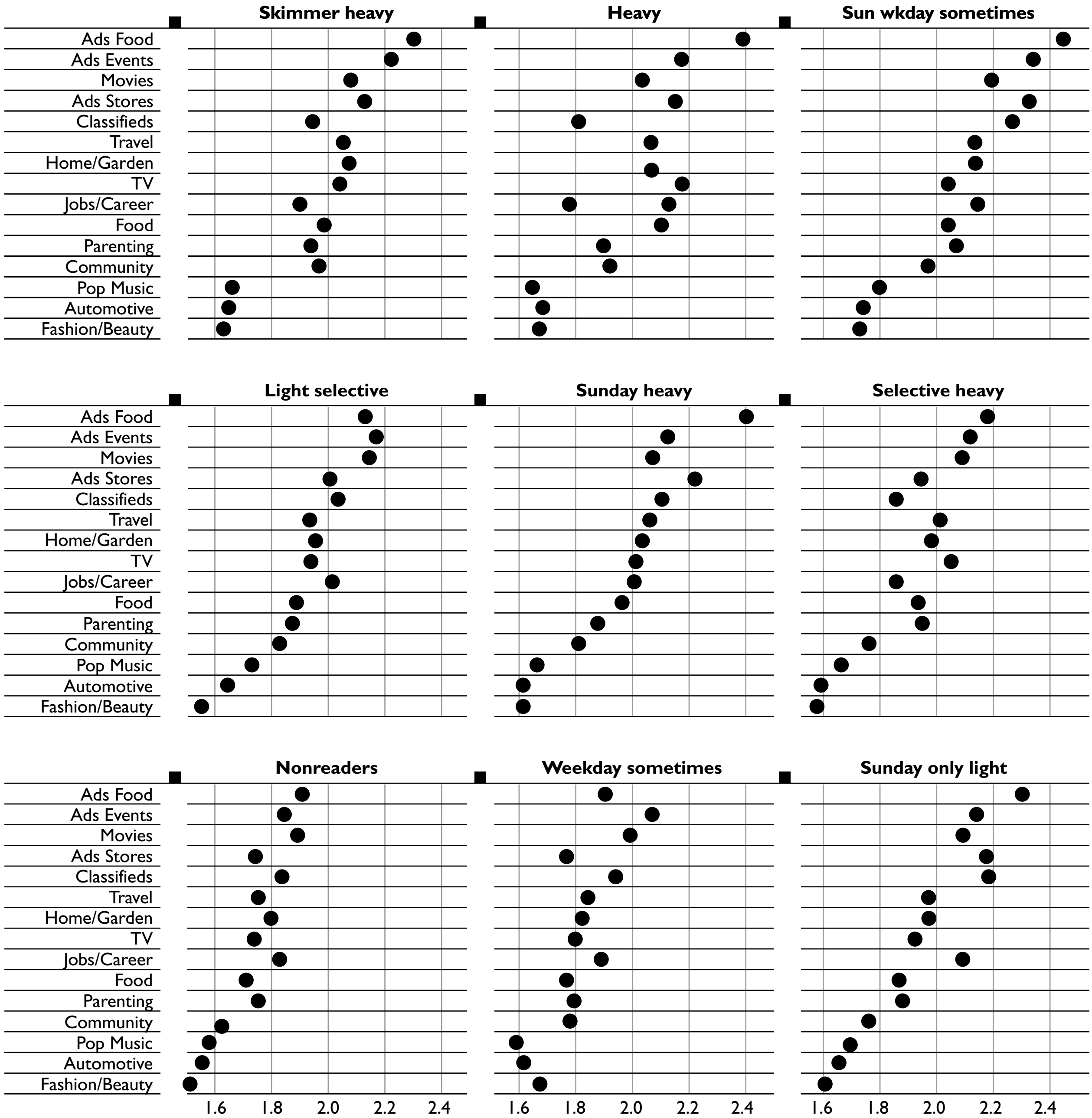
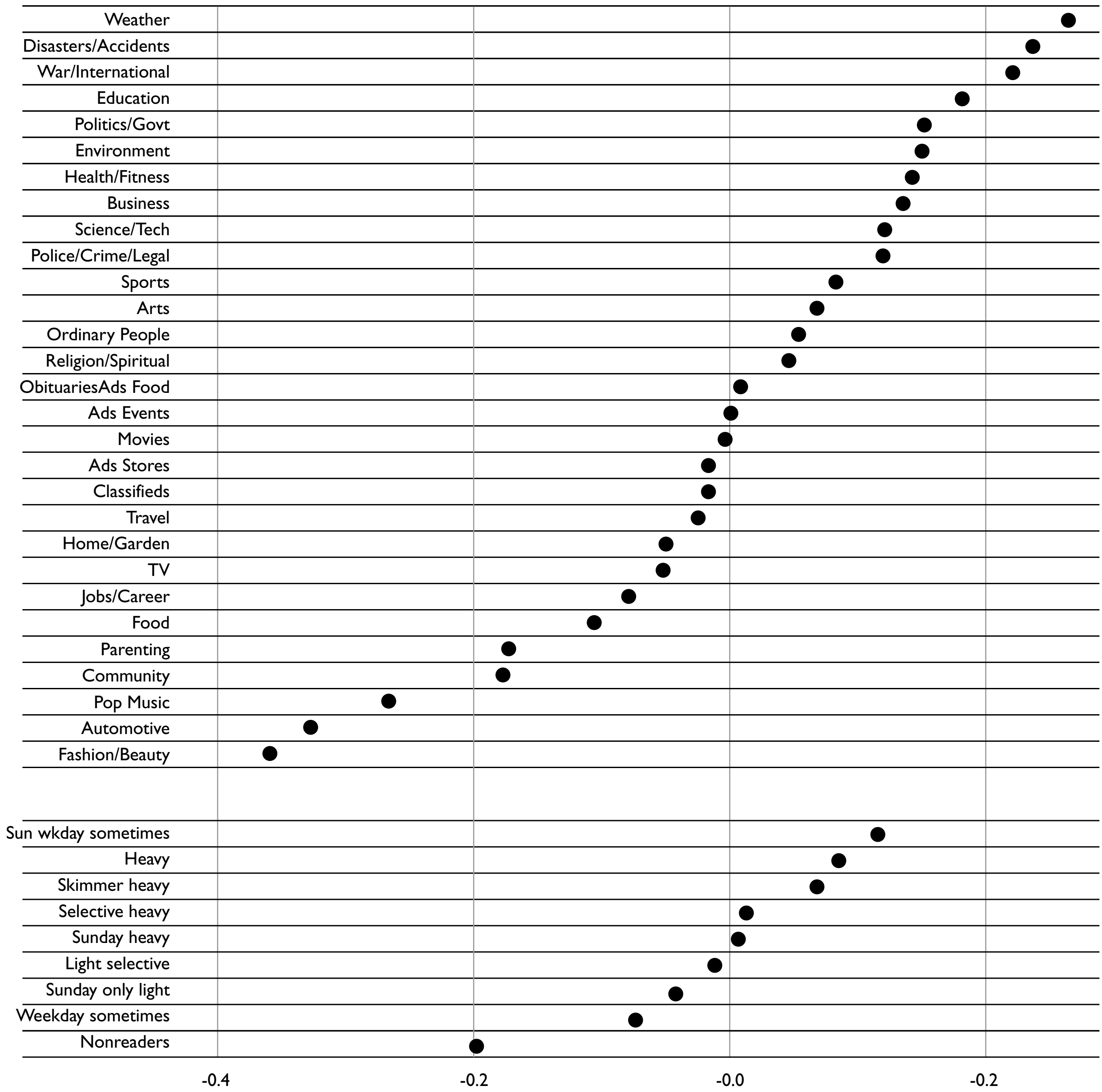


Figure 6: Main effect estimates (α_i and β_j) from ANOVA model showing which sections are most important overall and which RBTs give higher importance ratings



variable has the statistical advantage of being interval scaled. The qualitative variable has the advantage of adding qualitative interpretability. In this study the qualitative RBT scores reflect different points on the quantitative RBS continuum. RBT scores, as demonstrated, add information to the quantitative behaviour scores. In general, the particular manifestations of readership should depend on the intended use of the scale.

Additional information is also obtained in relating other variables to the qualitative RBTs in comparison to relying solely on the quantitative scores. For example, the percentage of female readers varies across RBTs, yet males and females have approximately equal average RBS values. Females read relatively more on Sundays while males read more on weekdays, but males and females are more commensurate on other manifestations of readership. Age varies more across RBTs than it does with RBS. Different RBTs have different content interests.

In short, when attempting to understand newspaper readership, and in our view consumption of other media, it is advisable to look across different manifestations of that behaviour both in terms of the quantitative level of the behaviour and the qualitative types of the behaviour. People read newspapers differently as well as to different extents. And these differences are associated with other variables in ways not apparent from looking just at the extent of readership. If a given newspaper is to increase readership, it must understand that there are many different ways of doing so. It could, for example, focus on getting a Heavy Selective reader to read more sections, a Heavy Skimmer reader to read more thoroughly, a Sunday Only reader to read during the week, a Weekend Only reader to read on Sundays, or a Nonreader to read. The tactics required to achieve these different strategies are likely to vary considerably. Because there is such heterogeneity among readers, a newspaper that focuses its efforts to increase readership on specific groups of readers should have a greater chance of success, since it can intervene in ways that are more relevant to the groups of interest.

It is our conclusion that any study of media consumption could examine both qualitative and quantitative behaviour scores and that this approach could enhance the interpretability and the scope of the results.

Figure 7: Residuals (e_{ij) from the ANOVA model for first group of variables

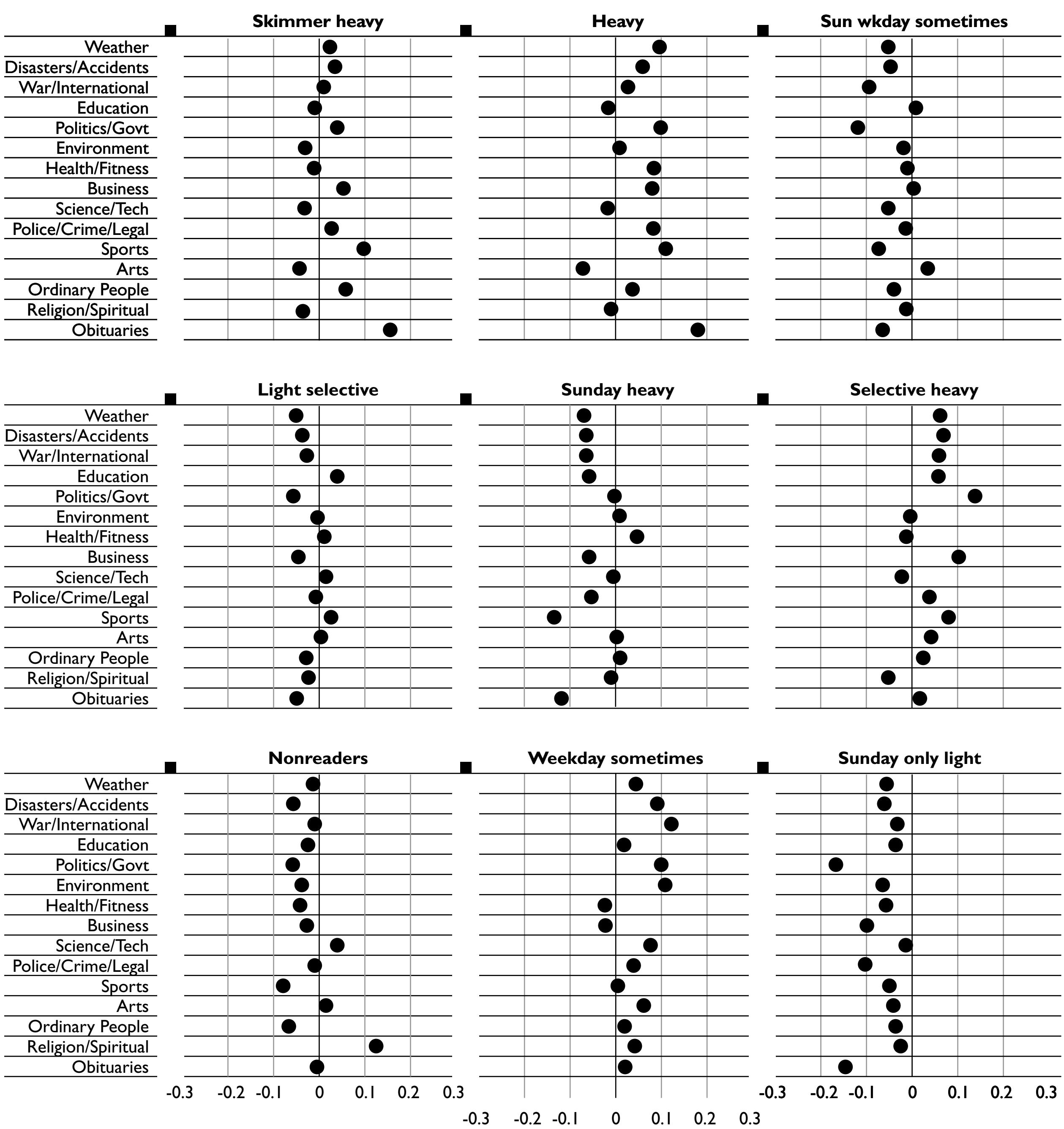
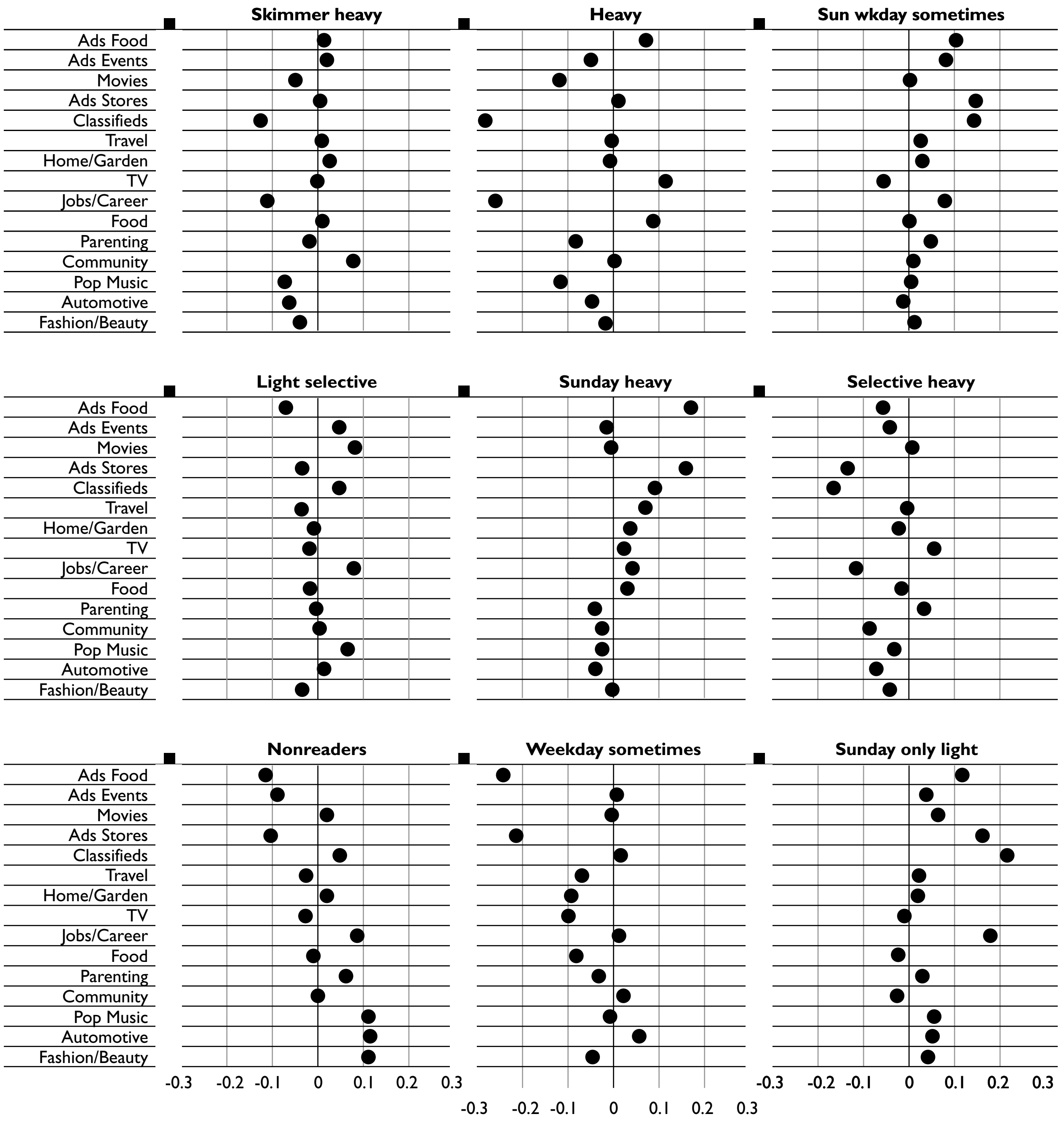


Figure 8: Residuals (e_{ij) from the ANOVA model for second group of variables



Endnotes

1 Also see http://readership.org/consumers/survey/main.htm.

2 Computing the means of the variables for each RBT is not straightforward because the latent classes are defined in terms of the response category bins whereas the PCA are defined using the original survey data. There are two obvious ways of estimating the class means, but both introduce noise. One approach is simply to average the original data by RBT, but this approach assumes that all posterior probabilities are either 0 or 1. The approach we follow involves mapping the response categories to specific responses on the questionnaire and then computing the mean of the conditional distribution using conditional probabilities ($\pi_{j|ik}$). For each variable we mapped the response category 0 to "do not read" box on the survey. Response category 1 is mapped to 16-30 minutes for weekday time, 1-11/2 hours for Sunday time, reading half the weekday issues, reading the Sunday paper, and reading 1/2 the newspaper for completion. Response category 2 is mapped to 46-60 minutes for weekday time, 2-21/2 hours for Sunday time, reading every weekday issue, and reading almost all/all of the newspaper.

3 We estimated "correlations" using a hierarchical linear model, also known as a random coefficient

model. Models were estimated using SAS proc mixed. We standardize age and the six manifestations to have mean 0 and standard deviation 1 in each market. We estimate the model $y_{ij} = b_i \text{age}_{ij} + e_{ij}$, where yij is a manifestation of readership for subject j in market i, age_{ij} is the age, b_i is the (random) slope for market i having mean β, and e_{ij} has mean 0 and variance σ^2. The reported "correlation" is β. Each of the β estimates were highly significant with $P<.0001$ and standard errors .0073, .0078, .0076, .0076, .0067, and .0067, respectively.

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